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**Controller Information Based
Identification for Unstable/Augmented
Aircraft**

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CONTROLLER INFORMATION BASED IDENTIFICATION FOR UNSTABLE/AUGMENTED AIRCRAFT

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Abstract

In this paper, the problem of parameter estimation for inherently unstable/augmented aircraft is addressed when information on controller is used in the procedure. A two step bootstrap method is presented.

1. Introduction

In this paper, the problem of parameter estimation of unstable/augmented aircraft is addressed when information on dynamics of controllers used for stabilising the unstable plant is available. Two approaches are possible to estimate the parameters of the aircraft operating in the Fly-by-Wire (FBW) mode:

(i) Equivalent parameters of the model between the command (overall) input and the output of the FBW-aircraft can be estimated. Since the feedback parameters are known, the parameters of the a/c math model can be retrieved from the equivalent parameters by suitable transformation. This method is feasible when the controller is a simple one'

(ii) In general, the FBW Control System (FBWCS) will be very complex and the retrieval of the aircraft math model parameters will not be feasible. For this case, a combined math model of the FBW-aircraft is postulated. Only the aircraft parameters are unknown and can be estimated. All the parameters of the FBWCS are assumed to be known. This leads to a huge state-space model of the combined system. When computer controllers are used, the order of the system increases. In such cases, the model reduction methods can be used to arrive at a reduced order model of the controller blocks and then used to arrive at a simpler combined model.

Here we investigate these two approaches and also present a Two Step Bootstrap Method (TSBM). This method can handle noisy input data and also circumvent the problem of handling large complex models. The method is essentially an extension of a two step method² (for transfer function estimation of an open loop plant from closed loop data) to state space parameter estimation. For generation and analysis of data, FTMATLAB is used.

2 Equivalent derivative estimation/retrieval approach (EQ/R)

The state space formulation of the plant is given as:

$$\begin{aligned} \dot{x} &= Ax + Bu + e \\ y &= Hx + v \end{aligned} \quad (1)$$

where x ($n \times 1$) state vector, u ($p \times 1$) input vector, y ($m \times 1$) measurement vector, e n -vector of zero mean Gaussian process noise with spectral density matrix Q , v m -vector of zero mean Gaussian measurement noise with covariance matrix R . Specifically consider short period dynamics:

$$\begin{bmatrix} \dot{w} \\ \dot{q} \end{bmatrix} = \begin{bmatrix} Z_w & u_0 + Z_q \\ M_w & M_q \end{bmatrix} \begin{bmatrix} w \\ q \end{bmatrix} + \begin{bmatrix} Z_{\delta_e} \\ M_{\delta_e} \end{bmatrix} \delta_e \quad (2)$$

where w is the vertical velocity, q the pitch rate and δ_e the elevator input (at K Fig. 1). The w signal is fed back to the input through a gain K_w so that the control law in this case is defined as

$$\delta_e = K_w w + \delta_p \quad (3)$$

where δ_p is the pilot command input at J (Fig. 1). Use of eq. (3) into eq. (2) results in:

$$\begin{bmatrix} \dot{w} \\ \dot{q} \end{bmatrix} = \begin{bmatrix} Z_w + K_w Z_{\delta_e} & u_0 + Z_q \\ M_w + K_w M_{\delta_e} & M_q \end{bmatrix} \begin{bmatrix} w \\ q \end{bmatrix} + \begin{bmatrix} Z_{\delta_e} \\ M_{\delta_e} \end{bmatrix} \delta_p \quad (4)$$

Thus we see that due to the augmentation, the coefficients in the first column of the matrix A are affected. It is required to estimate the elements of the matrices A and B in eq. (2,4). The math model for parameter estimation could be formulated as:

$$\begin{bmatrix} \dot{w} \\ \dot{q} \end{bmatrix} = \begin{bmatrix} Z_{eq} & u_0 + Z_q \\ M_{eq} & M_q \end{bmatrix} \begin{bmatrix} w \\ q \end{bmatrix} + \begin{bmatrix} Z_{\delta_e} \\ M_{\delta_e} \end{bmatrix} \delta_p \quad (5)$$

Using the pilot command δ_p and the measured output y , the parameters in eq. (5) can be estimated. The derivatives Z_w and M_w of the plant can be computed from Z_{eq} and M_{eq} using the known value of the feedback gain K_w and estimates of Z_{δ_e} and M_{δ_e} . For this case input noise at 'K' (in Fig. 1) is not considered.

Case 2.1: For numerical validation, simulated data of a simplified model of BEAVER aircraft are generated with a sampling time of 0.05 sec and 10 sec duration. In order to study the effect of the gain K_w on the parameter estimates, five sets of data are generated by varying the feedback gain. Table 1 gives the equivalent derivatives estimated using Output error method (OEM). The relative parameter estimation error norm (PEEN) is defined as follows:

$$PEEN \% = 100 * \text{norm}(b_t - b_e, 2) / \text{norm}(b_t, 2) \quad (6)$$

where b_t = vector of true parameters, b_e = vector of estimated parameters. Once the equivalent derivatives are estimated, the parameters of the plant are retrieved using the known feedback gain values. It is clear that parameter estimates are fairly accurate when the gain K_w is small. This establishes that for known and simple feedback loops, the plant parameters can be retrieved easily and with reasonable accuracy when the feedback gains are small.

3. Controller augmented modelling approach (CAM)

When the controller parameters (gain and time constants) are known, they can be used to develop the total math model of the augmented system. This method can be used when the controller is complex as well as simple. The order of the math model will depend on the complexity of the controller used. The controller related parameters are kept fixed in the model since they are assumed to be known, and only the plant parameters are estimated. This can be ascertained by using the plant model of eq. (2) and feedback law of eq. (3), to arrive at eq. (4), wherein the numerical value of the feedback gain is assumed to be known and substituted before the complete model is used for parameter estimation. In order to see the complexity involved, the fourth order longitudinal

dynamics of an aircraft with the associated controller blocks (Fig. 2) is considered. The state equations of the unaugmented plant are described by

$$\begin{bmatrix} \dot{\alpha} \\ \dot{q} \\ \dot{\theta} \\ \dot{v/v_0} \end{bmatrix} = \begin{bmatrix} Z_\alpha & 1 & 0 & Z_{v/v_0} \\ M_\alpha & M_q & 0 & M_{v/v_0} \\ 0 & 1 & 0 & 0 \\ X_\alpha & 0 & X_\theta & X_{v/v_0} \end{bmatrix} \begin{bmatrix} \alpha \\ q \\ \theta \\ v/v_0 \end{bmatrix} + \begin{bmatrix} Z_{\delta_e} \\ M_{\delta_e} \\ 0 \\ X_{\delta_e} \end{bmatrix} \delta_e \quad (7)$$

The total model (based on blocks 1, 3-7) is obtained as:

$$\begin{bmatrix} \dot{\alpha} \\ \dot{q} \\ \dot{\theta} \\ \dot{v/v_0} \\ \dot{\delta_e} \\ \dot{cs_1} \\ \dot{cs_2} \\ \dot{cs_3} \\ \dot{cs_4} \\ \dot{cs_5} \end{bmatrix} = \begin{bmatrix} Z_\alpha & 1 & 0 & Z_{v/v_0} & Z_\delta k_{1,1} & 0 & 0 & 0 & 0 & 0 \\ M_\alpha & M_q & 0 & M_{v/v_0} & M_\delta k_{1,2} & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ X_\alpha & 0 & X_\theta & X_{v/v_0} & X_\delta k_{1,3} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & a_{53} & a_{54} & -k_{1,3} & a_{56} & a_{57} & a_{58} & a_{59} & a_{510} \\ 0 & 0 & 0 & 0 & 0 & a_{66} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & a_{77} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & a_{88} & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & a_{99} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & a_{100} \end{bmatrix} \begin{bmatrix} \alpha \\ q \\ \theta \\ v/v_0 \\ \delta_e \\ cs_1 \\ cs_2 \\ cs_3 \\ cs_4 \\ cs_5 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \delta_p \quad (8)$$

Eq. (8) is arrived at by utilising functions BLKBUILD and CONNECT of PC MATLAB, to simulate the closed loop system of Fig. 2. In eq. (8), the cs_i are the controller related intermediate state variables. The K_j and a_{ij} are known constants which implicitly contain the time constant/gains of the controller transfer functions. Next, numerical validation of CAM, is presented.

Case 3.1: The same data (eqs. (2), (3)) (with SNR=∞) used in section 2 are used for numerical validation. In this case the controller has a simple structure. The known gain K_w is kept fixed in the model and the total model between the input r and the output y is identified. The math model described in eq. (4) is used for estimating the parameters of the plant. The OEM is used for analysis of the data since the overall system is stable. In Fig. 3 some of the parameters estimated using CAM and EQ/R method are compared. It is clear that the two methods give identical results for at least simple plant. It is seen from Fig. 4 that the estimates of M_w deviate from the true values, despite utilising the known controller gain in the model. The PEEN also increases. Perhaps, the increasing gains bring about more correlations in the data.

Case 3.2: Fourth order longitudinal dynamics of a typical fighter aircraft and the associated controller

blocks of Fig. 2 are used to generate the data. The basic plant dynamics are described by eq. (7) and the total model used for parameter estimation is given by eq. (8). All the controller related parameters are kept fixed at the known values and estimates of nine aerodynamic derivatives of the plant are shown in Table 2. Almost all the parameters are estimated close to the true values, indicating the viability of this method for parameter estimation of unstable/augmented systems, when the controller information is known. When the controller is of a higher order complexity, the use of CAM would lead to higher order models of the augmented system with many zeros in the state space matrices of the model. This might lead to stiff system of equations for integration. This is clear from Table 3 which gives the eigenvalues and condition number of the open loop/closed loop system. The condition number of the closed loop system is very high indicative of the ill conditioning problem that could occur if the order of the system is increased further.

4. Covariance Analysis of system operating under feedback

It is to be noted here that when direct identification using measured input and output data (at K and L) is attempted, the correlation between the plant input u and the output noise v might lead to biased estimates. Also, the signal, u , could be noisy. This will lead to input/output noise correlations in addition to the signal/noise correlation. To bring about clearly and the complexities involved, due to these correlations, the expressions for the covariance matrix are derived in this section considering two approaches: (i) open loop system with input noise and (ii) closed loop system with input noise.

4.1 Open loop system with input noise

To carry out the analysis, the system of eq. (1) is considered in discrete form:

$$x_{j+1} = \phi_j x_j + B_j u_j + \Gamma_j e_j \quad (9)$$

$$y_j = H_j x_j + v_j \quad (10)$$

$$\text{Also, } E\{x_0\} = \hat{x}_0; \quad P_0 = E\{(\hat{x}_0 - x_0)(\hat{x}_0 - x_0)^T\};$$

$$E\{v_j e_k^T\} = 0; \quad \hat{x}(0) = \hat{x}_0; \quad P(0) = P_0 \quad (11)$$

where ' $\hat{\cdot}$ ' denotes estimated values and E the mathematical expectation.

Since the input signal u is assumed to be noisy, it can be written as

$$u_j = u_{d_j} + u_{n_j} \quad (12)$$

where u_{d_j} denotes the deterministic part of the input signal and u_{n_j} denotes the noise part.

Using eq. (12) in eq. (9), we get,

$$x_{j+1} = \phi_j x_j + B_j u_{d_j} + B_j u_{n_j} + \Gamma_j e_j \quad (13)$$

The last two terms in eq. (13) could be combined:

$$\begin{aligned} x_{j+1} &= \phi_j x_j + B_j u_{d_j} + [B_j \quad \Gamma_j] \begin{bmatrix} u_{n_j} \\ e_j \end{bmatrix} \\ &= \phi_j x_j + B_j u_{d_j} + \Gamma_{aj} e_{aj} \end{aligned} \quad (14)$$

where the subscript 'a' denotes the augmented effect (the input noise as part of the process noise).

The error in the estimates at instant j is given by

$$\tilde{x}_j = \hat{x}_j - x_j \quad (15)$$

and the covariance matrix of estimation error is given by

$$P_j = E\{\tilde{x}_j \tilde{x}_j^T\} \quad (16)$$

The error covariance matrix at instant $j+1$ is to be obtained given the fact that we know its value at instant j . We have the state estimate⁴ propagating from instant j to $j+1$ via the transition matrix ϕ_j given by:

$$\hat{x}_{j+1} = \phi_j \hat{x}_j + B_j u_j \quad (17)$$

The estimation error at instant $j+1$ is given by

$$\begin{aligned} \tilde{x}_{j+1} &= \hat{x}_{j+1} - x_{j+1} \\ &= \phi_j \tilde{x}_j - \Gamma_{aj} e_{aj} \end{aligned} \quad (18)$$

The estimation error covariance matrix at $j+1$ is:

$$\begin{aligned} P_{j+1} &= E\{\tilde{x}_{j+1} \tilde{x}_{j+1}^T\} \\ &= E\{[\phi_j \tilde{x}_j - \Gamma_{aj} e_{aj}][\phi_j \tilde{x}_j - \Gamma_{aj} e_{aj}]^T\} \end{aligned} \quad (19)$$

Since the estimation error and the (equivalent) process noise e_{aj} are assumed to be uncorrelated, we get

$$P_{j+1} = \phi_j P_j \phi_j^T + \Gamma_j Q \Gamma_j^T + \Gamma_{aj} Q_{ea} \Gamma_{aj}^T \quad (20)$$

where the subscript ' $e_a e_a$ ' is used to indicate augmented input noise covariance matrix. From eq. (20), it is clear that, when the input is noisy, the statistics of the additional terms have to be included in the covariance computations which affect the Kalman gain computations in the measurement update part of the filter.

4.2 Closed loop system with input noise

When the output y is fed back, the output noise v gets correlated with the input signal u and affects the covariance computations. Let the pilot input be r , the feedback matrix be G and the input noise be u_{nj} . Input u can be written as:

$$u_j = r_j + G v_j + u_{nj} \quad (21)$$

Substituting for y from eq. (1) we have,

$$u_j = r_j + G H x_j + G v_j + u_{nj} \quad (22)$$

Using eq. (22) in eq. (9), we get,

$$x_{j+1} = \phi_j x_j + B_j r_j + (B_j G H) x_j + (B_j G) v_j + (B_j G) u_{nj} + \Gamma_j e_j \\ = (\phi_j + B_j G H) x_j + B_j r_j + (B_j G) v_j + \Gamma_{aj} e_{aj} \quad (23)$$

and the estimate at instant $(j+1)$ is given by:

$$x_{j+1} = (\phi_j + B_j G H) x_j + B_j r_j \quad (24)$$

Using eqs. (23) and (24), the estimation error can be written as:

$$\tilde{x}_{j+1} = (\phi_j + B_j G H) \tilde{x}_j - B_j G v_j - \Gamma_{aj} e_{aj} \quad (25)$$

The estimation error and the process noise, the measurement noise and estimation error are assumed to be uncorrelated. Hence we get

$$P_{j+1} = (\phi_j + B_j G H) P_j (\phi_j + B_j G H)^T + \Gamma_{aj} Q_{ea} \Gamma_{aj}^T + (B_j G) R (B_j G)^T \quad (26)$$

Additional term due to the measurement noise covariance is present when there is feedback and this introduces more uncertainty in the filter computations. Also, the first term involving the transition matrix has an extra term due to the feedback

5 Two Step Bootstrap Method (TSBM)

An alternative approach is suggested which is based on a two step method for transfer function estimation of a linear plant². For a SISO plant, we have:

$$y(t) = G_0(q)u(t) + v(t) \quad (27)$$

where $G_0(q)$ is the plant transfer function. The input signal $u(t)$ is determined by

$$u(t) = r(t) - C(q)v(t) \quad (28)$$

where $C(q)$ represents a linear controller. Since u and v are correlated it is difficult to estimate the plant transfer function consistently. The sensitivity function of the closed loop system is given by

$$T_0(q) = 1 / (1 + G_0(q)C(q)) \quad (29)$$

using $T_0(q)$, eqs. (27) and (28) can be written as

$$u(t) = T_0(q)r(t) - C(q)T_0(q)v(t) \quad (30)$$

$$y(t) = G_0(q)u(t) + v(t) \quad (31)$$

Since r and v are uncorrelated signals and u and r are available from measurements, the $T_0(q)$ can be identified in an open loop way. Using the estimated $T_0(q)$ we can write

$$\tilde{u}(t) = T_0(q)r(t) \quad (32)$$

$$y(t) = G_0(q)\tilde{u}(t) + T_0(q)v(t) \quad (33)$$

Since \tilde{u} and v are uncorrelated, $G_0(q)$ can be estimated in an open loop way. It is clear from eq. (32) that, in the first step, to identify the sensitivity function, only the input reference signal is used. The identification is performed by applying either an FIR (finite impulse response) model structure having a sufficient polynomial degree to approximate the dynamics of the sensitivity function or a finite number of orthogonal functions. The other alternative would be to find out by trial and error, the best transfer function (i.e. numerator denominator polynomials) that fit the measured input signal u . In the proposed two step method, an effective use of the pilot input signal r , output data y and the available controller information is made at the first step to obtain the predicted input signal \tilde{u} .

First step:

Using all available measurements of $u(t)$, $r(t)$ and $y(t)$ the problem is to obtain an estimate of the input signal. This could be done by formulating a Least squares (LS) estimation problem by treating the measured input ' u ' to the aircraft as the output of the LS model and the measured data ' y ' which are feedback as the input to the LS model. Using subscript ' m ' to denote measured data we have,

$$U_m = R - kY_m \quad (34)$$

where U is the (pxN) control input measurement matrix. R the (pxN) pilot command input, k (pxj) unknown parameter vector to be estimated and Y the (jxN) measurement matrix. However, since the measurements are noisy, eq. (34) can be written as

$$U_t + U_n = R - k(Y_t + F_n) \quad (35)$$

where the subscript 't' denotes true value and 'n' the measurement noise or

$$U_t = R - kY_t - kY_n - U_n = R - kY_t + U_{nn} \quad (36)$$

where U_{nn} denotes the compound noise. The effect of this noise is minimised in the first step to obtain the model that best approximates the input (of the plant) using the measurements of the output and the pilot command input. In case the feedback is complex, the model could be formulated as:

$$U = f(Y_m, Y_m, R, R) + \text{noise} \quad (37)$$

The time derivative terms could be obtained by numerical differentiation and the appropriate terms could be added to formulate a LS model that is linear in parameters. The model is obtained by minimising the cost function:

$$J = \frac{1}{2} \sum_{i=1}^N [u_i - f(y_{mi}, \dot{y}_{mi}, r_i, \dot{r}_i)]^2 \quad (38)$$

The function 'f' can be suitably parameterised by having an appropriate regression model and the cost function J is minimised to estimate the regression model coefficients.

Second Step

Once the model that best fits the data is obtained, the estimated coefficients are used in the UD factorisation based Kalman filter" in the second step to estimate the plant parameters as follows:

Time propagation

$$\hat{x}_{j+1}^* = \phi_j \hat{x}_j + B_j \hat{u}_j \quad (39)$$

$$P_{j+1}^* = \phi_j P_j \phi_j^T + \Gamma_j Q \Gamma_j^T \quad (40)$$

Here ' x ' is augmented with unknown parameter vector and '*' denotes predicted signals.

Measurement update

The parameter estimates are obtained by using the current measurement and the predicted state as follows

$$\hat{y}_{j+1}^* = H_{j+1} \hat{x}_{j+1}^* \quad (41)$$

State update

$$\hat{x}_{j+1} = \hat{x}_{j+1}^* + K_{j+1} (z_{j+1} - \hat{y}_{j+1}^*) \quad (42)$$

Covariance update

$$\hat{P}_{j+1} = (I - K_{j+1} H_{j+1}) P_{j+1}^* \quad (43)$$

Kalman gain

$$K_{j+1} = P_{j+1}^* H_{j+1}^T (H_{j+1} P_{j+1}^* H_{j+1}^T + R)^{-1} \quad (44)$$

Estimated input

$$\hat{u} = k_m \hat{y}_{j+1}^* + k_{dm} \hat{y}_{j+1}^* + k_r r + k_{dr} \dot{r} \quad (45)$$

The feature of this procedure is that the coefficients estimated in the first step, the filtered measurements and input signals are used. As an illustration, the longitudinal dynamics of an aircraft (Fig. 2), described by the following equations are considered:

State model:

$$\dot{\alpha} = Z_\alpha \alpha + q + Z_{v/v_0} (v/v_0) + Z_{\delta_e} \hat{\delta}_e \quad (46a)$$

$$\dot{q} = M_\alpha \alpha + M_q q + M_{v/v_0} (v/v_0) + M_{\delta_e} \hat{\delta}_e \quad (46b)$$

$$\dot{\theta} = q \quad (46c)$$

$$\dot{v/v_0} = X_\alpha \alpha + X_\theta \theta + X_{v/v_0} (v/v_0) + X_{\delta_e} \hat{\delta}_e \quad (46d)$$

Measurement model:

$$\alpha_m = \alpha \quad (47a)$$

$$q_m = q \quad (47b)$$

$$\theta_m = \theta \quad (47c)$$

$$(v/v_0)_m = (v/v_0) \quad (47d)$$

Since the feedback structure is complex (Fig. 2), to obtain an estimate of the control surface deflection, the measurements of the feedback signals α , q and n_z and their time derivatives (obtained by numerical differentiation), are also used in model building in the first step of the TSBM procedure.

$$\dot{\delta}_{e_m} = K_1 \alpha_m + K_2 q_m + A_3 \dot{\alpha}_m + K_4 \delta_p + K_5 \alpha + K_6 q + K_7 \dot{\delta}_p \quad (48)$$

The estimated coefficients are then used to obtain the

$\hat{\delta}_e$ by appending the following equation to the state eqs. (45-46) for the Kalman UD filtering:

$$\delta_e = K_1 \alpha + K_2 q + K_3 \dot{\alpha} + K_4 \delta_p + K_5 \alpha + K_6 q + K_7 \dot{\delta}_p \quad (49)$$

The feature of the bootstrap procedure is that the predicted states, measurements and their derivatives are available at every instant in the filter.

Case 4.1: (case 3.1) In the first step, the following model was used to fit the data between the input signal and the output and the gain parameter k was estimated.

$$\delta_{e_m} = kw_m + \delta_p \quad (50)$$

The estimated value of k is used in the bootstrap manner in the second step and the results of TSBM are shown in Table 4. For comparison the data was analysed using the direct identification between δ_e and y (points K and L in Fig. 1) and the CAM approach (points J and L in Fig. 1). It can be seen that the TSBM gives improved parameter estimates as compared to the direct method and as good as by CAM

Case 4.2: (Case 3.2) Eq. (48) is used as a model to fit δ_e signal. The coefficients K_1 to b_7 estimated in step 1 were used in the second step as in eq. (49). Four models were tried to arrive at the best model that fits the data. Model selection was based both on the qualitative comparison of fit and reduction in percentage fit error. Fig. 5 shows comparison of the estimated and measured inputs for the four models tried. It is to be emphasised here that the indirect use of the knowledge of the controller at the model building step, aids in generating reasonably good estimate of input signal.

The parameter estimation results using TSBM are shown in Table 5 and compared with the CAM and direct estimates. Best results are obtained with CAM. However, it requires the use of complex math models. The TSBM does provide a good alternative especially when the input is very noisy and it does not involve the complex higher order models as in the case CAM for this example. Improved models at the first stage could lead to better estimates. Fig. 6 shows the comparison of the PEENs for all the cases listed in Tables 4 and 5. Significant improvement is observed in case 4.2 for SNR=10, wherein the results of using TSBM show that they are comparable to the case when SNR= ∞ . Fig. 7 gives the control surface inputs used in direct, controller augmented and TSBM methods and one of the parameter estimates compared with the true value. From Fig. 7, it is evident that the TSBM gives

improved performance as compared to the direct method when the input is noisy.

6. Concluding remarks

From the results of this paper, it can be inferred that amongst the CIBIM methods, the CAM wherein the controller parameters are used in the total estimation math model gives the best results. However, if the model complexity increases, one may end up with stiff differential equations. The TSBM proposed in this paper, overcomes this problem by solving the parameter estimation in two steps. It also has the additional advantage of being able to handle noisy input signals at the controller surface and in most cases yields results better than the direct method. Further analysis and improvements are envisaged.

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Table 1 Parameter Estimates using EQ/R
(Case 2.1, SNR=∞, SP)

PARAM	$K_w \rightarrow$ TV ↓	0.025	0.05	0.25	0.5	1.0
Z_w		-1.58	-1.73	-3.01	-4.68	-8.24
$+K_w Z_{\delta_e}$						
$Z_w \#$	-1.43	-1.42	-1.41	-1.39	-1.35	-1.28
Z_{δ_e}	-6.26	-6.33	-6.40	-6.49	-6.66	-6.96
M_w		-0.10	-0.42	-3.01	-6.31	-13.5
$+K_w M_{\delta_e}$						
$M_w \#$	0.22	0.22	0.21	0.25	0.31	0.44
M_q	-3.71	-3.72	-3.72	-3.67	-3.52	-2.89
M_{δ_e}	-12.8	-12.8	-12.8	-13.0	-13.2	-13.9
PEEN%	-	0.67	0.76	1.67	2.94	6.69

(# retrieved from equivalent derivatives)

Table 3 Eigen values of the open loop/closed loop system (case 3.2)

EV (λ_i) and CN	OLP	CLTV	CLES1	CLES2
λ_1	-1.492	-7.8± j8.23	-7.9± j8.49	-7.7± j7.89
λ_2	0.251	-9.913	-9.72	-10.136
λ_3	-0.352	-3.606	-3.61	-3.605
λ_4	-0.046	-3.259	-3.26	-3.259
λ_5		-0.792	-0.791	-0.749
λ_6		-0.01± j0.09	-0.01± j0.09	0.002± j.09
λ_7		-0.406	-0.404	-0.405
λ_8		-4.00	-4.00	-4.00
CN	68.36	8488	8655	7933

CLTV Closed loop true values

CLES1 Closed loop estimated values (SNR=∞)

CLES2 Closed loop estimated values (SNR=10)

OLP Open loop plant//PARAM Parameters

(.) Standard deviation//TV True value

EV Eigen value//CN Condition number

Table 2 Parameter estimates using CAM
(Case 3.2, SNR=∞, fourth order model)

PARAM	TV	OEM
$Z_{\alpha} v0$	-0.4193	-0.4195 (0.14)
Z_{δ_e}	-0.1147	-0.1468 (0.52)
$Z_v v0$	-0.1955	-0.1905 (0.67)
M_{α}	1.3316	1.3418 (0.20)
M_q	-0.4716	-0.4641 (0.23)
M_{δ_e}	-4.827	-4.863 (0.06)
X_{α}	-0.0965	-0.0954 (0.11)
$X_v v0$	-0.0443	-0.0459 (0.35)
X_{δ_e}	-0.8599	-0.8802 (0.08)
PEEN%	-	1.1098

Table 4 Comparison of Parameter Estimates
(Case 4.1)

PARAM	TV	SNR=10		
		DIRECT	CAM	TSBM
Z_w	-1.4249	-1.3452	-1.3643	-1.3643
Z_{δ_e}	-6.2632	-5.9920	-5.9755	-5.9755
M_w	-0.1	-0.1220	-0.1177	-0.1177
M_q	-3.7067	-3.3123	-3.3545	-3.3545
M_{δ_e}	-12.784	-11.572	-11.712	-11.712
PEEN%	-	8.8307	7.8899	7.8899

**Table 5. Comparison of Parameter Estimates
(Case 4.2)**

PARAM	TV	SNR=10		
		DIRECT	CAM	TSBM
Z_{α}	-0.771	-0.7700	-0.7276	-0.6840
$Z_{v/v0}$	-0.1905	-0.2177	-0.2013	-0.0707
Z_{δ_e}	-0.2959	-0.2942	-0.2568	-0.1433
M_{α}	0.3794	0.2409	0.3091	0.5596
M_q	-0.832	-0.7621	-0.7716	-1.0129
$M_{v/v0}$	0.0116	-0.0046	0.0103	0.0111
M_{δ_e}	-9.6952	-7.7856	-9.4710	-9.1207
X_{α}	-0.0937	-0.3234	-0.1062	-0.0463
X_{θ}	-0.0961	-0.0619	-0.0952	-0.1427
$X_{v/v0}$	-0.0296	-0.0121	-0.0168	-0.0648
X_{δ_e}	-0.0422	-0.0363	-0.0400	-0.0393
PEEN%	-	19.7447	2.5616	4.5290

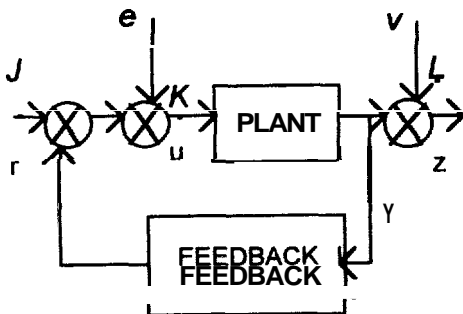


Fig. 1. Block diagram of closed loop system

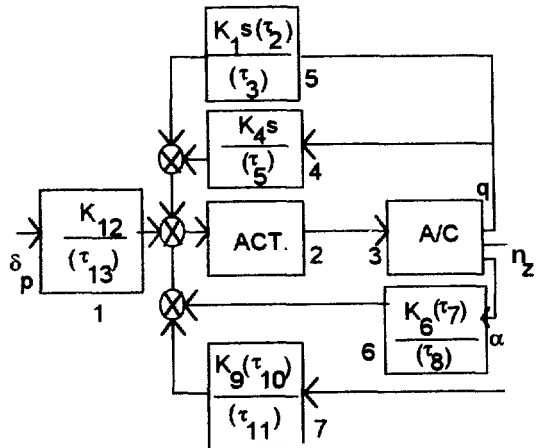
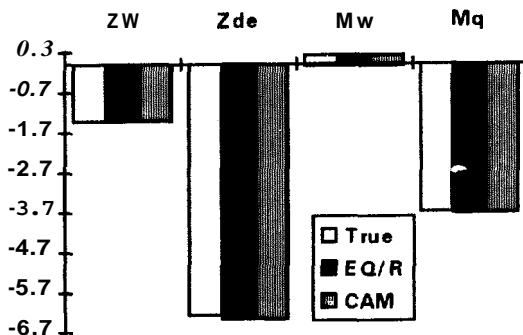


Fig. 2 Block diagram of a typical control system

e.g. $\frac{K_1 s(\tau_2)}{(\tau_3)} = \frac{K_1 s(1+K_2 s)}{(1+K_3 s)}$



**Fig. 3 Parameter estimates using EQ/R and CAM
(Case 2.1/3.1)**

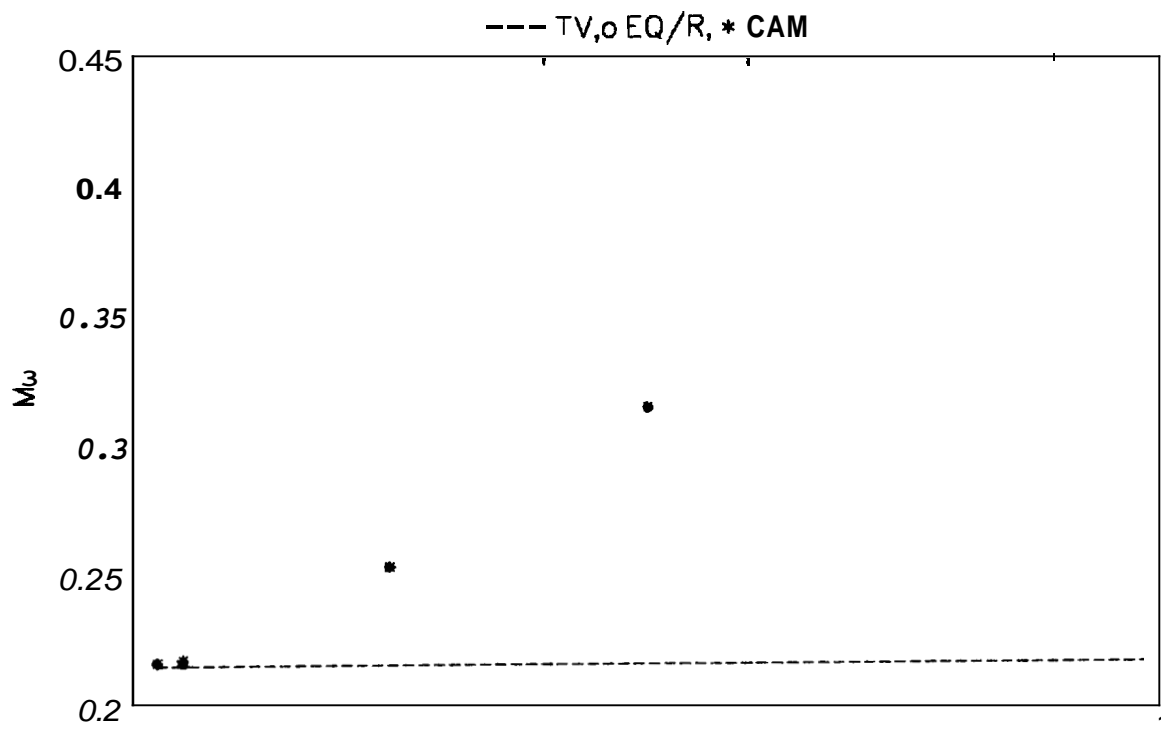
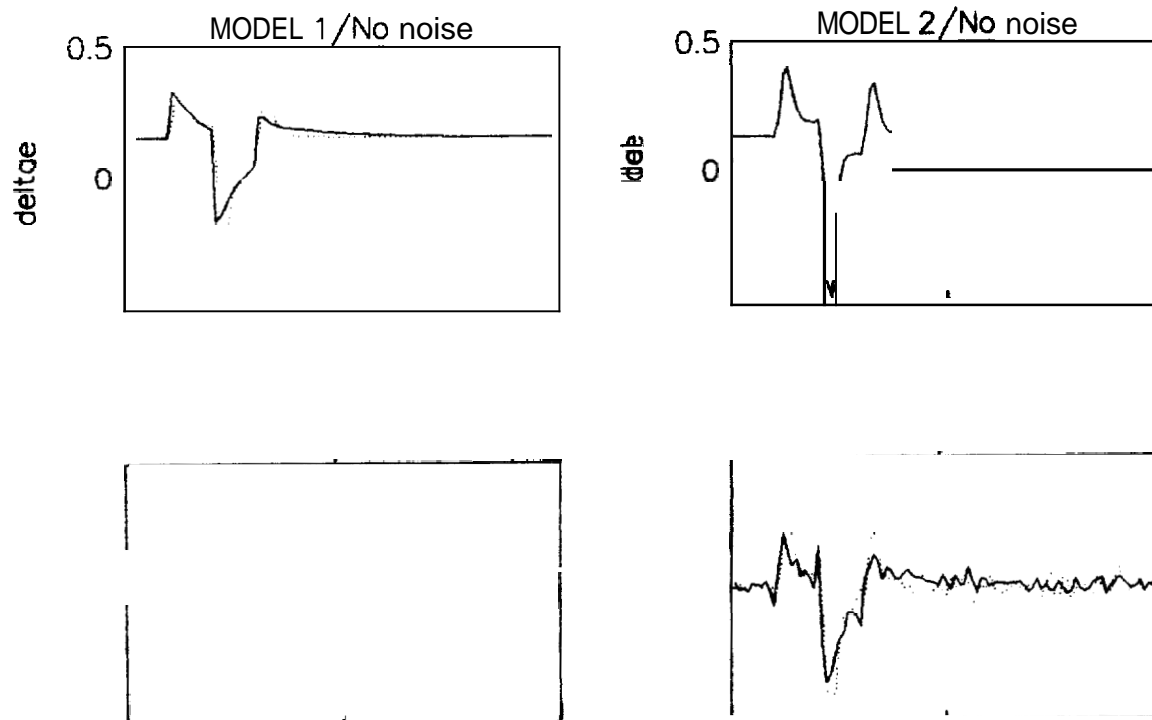


Fig. 4 Effect of gain (K_w) on the estimate (no noise)



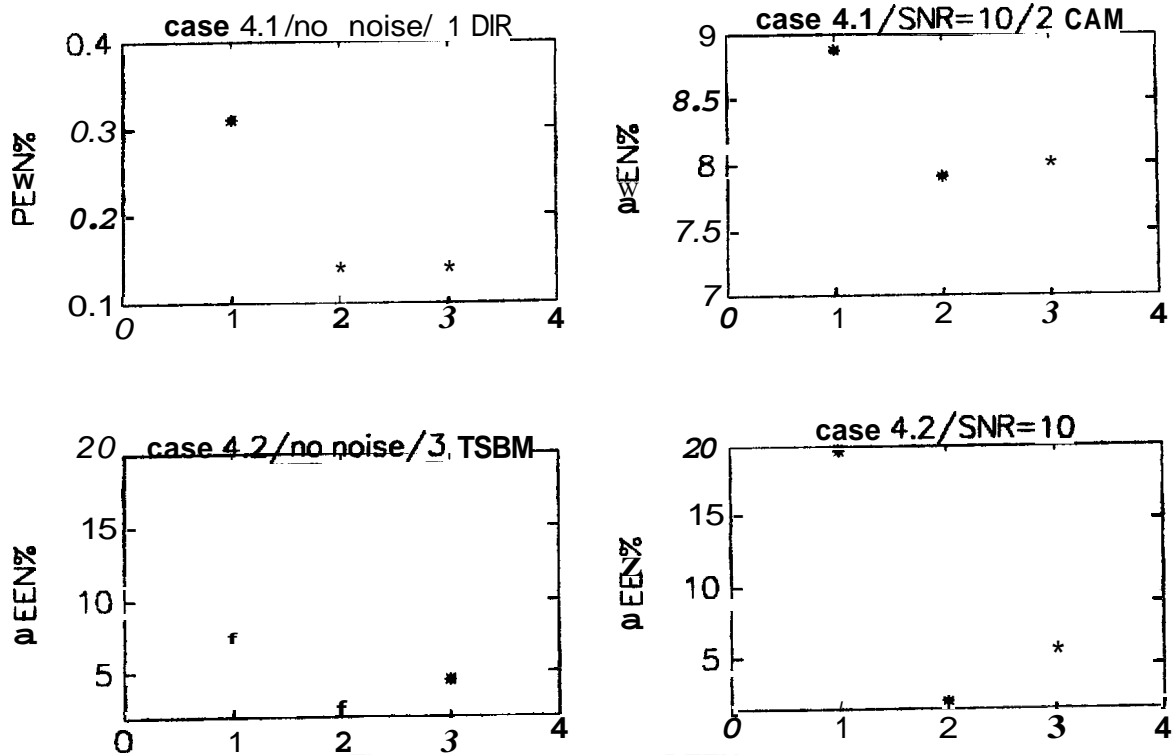


Fig. 6 Comparison of PEENs

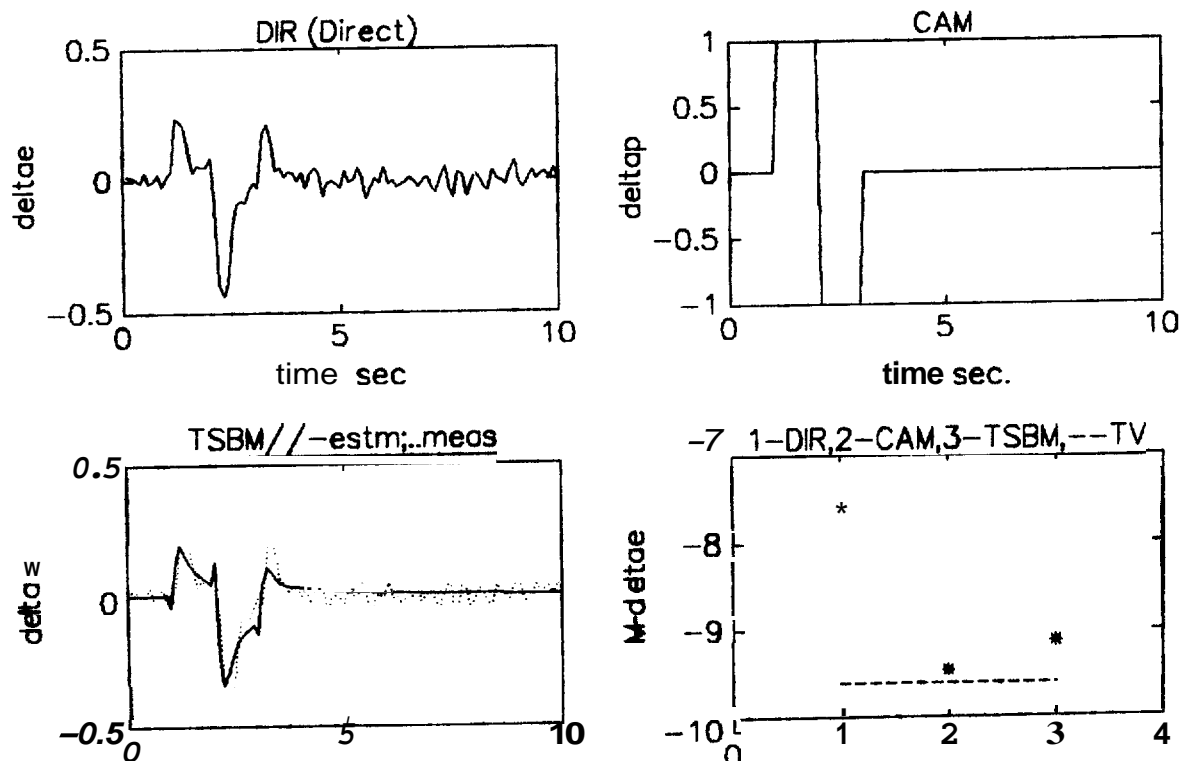


Fig. 7 Comparison of inputs and parameter estimates



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